



Impact of drought on vegetation carbon storage in arid and semi-arid regions

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ABSTRACT

Drought is a common phenomenon in arid and semi-arid regions. In global carbon cycle, semi-arid ecosystem plays a crucial role in interannual variability and greening trend. The vegetation carbon storage and its relation with drought in India are not well understood. The impact of drought on vegetation carbon storage is investigated using Standardized Precipitation Evapotranspiration Index (SPEI) and CASA (Carnegie-Ames-Stanford Approach) derived Net Primary Production (NPP) during 2001–2013. A strong positive correlation is found between regional NPP and SPEI. CASA derived NPP shows good agreement ($R^2 = 0.57$, significance > 95%) with field based observation in arid and semi-arid regions of Gujarat. A significant Increasing trend of 0.2 TgC Yr^{-1} (about 2 % per year) is observed during the period of 2001–2013. The highest decreased of 24% (2.79 TgC Yr^{-1}) in NPP was found during 2002 and a notable increase of 17% (1.61 TgC Yr^{-1}) was seen during 2013 due to consecutive drought and surplus rainfall years respectively. The study suggests that consecutive droughts have brought an immense impact on vegetation productivity. During the drought years, dry sub-humid region was the most vulnerable as it was dominated by agriculture land, while semi-arid region was less affected due to forest cover. Despite many droughts, some part of north-west and south-west regions had shown an increase in vegetation carbon storage, which indicates that these parts are not affected by the drought. The study also suggests that in addition to rainfall, heat wave also played a major limiting factor in vegetation productivity. The study will be useful in identifying the regions which are more vulnerable to drought. Present study, will also be helpful in combating the regional climate change as vegetation carbon storage is directly linked with agricultural productivity.

1. Introduction

Reduction in rainfall over an extended period of time (usually season or more in length) is considered as drought. In India, normally droughts exhibit due to delay or early onset of southwest monsoon (June–September) along with poor precipitation (Lindsey, 2012). Arid and semi-arid regions are more responsive to drought, as arid and semi-arid climate are more sensitive to deficiency in rainfall and temperature extremes (Bhuiyan, 2008). In 21st-century, extreme climate events are amplified in frequency and magnitude (Parry et al., 2007). After industrial revolution, the increasing trend of atmospheric carbon dioxide is considered as primary reason for global warming (Alexander et al., 2000). Terrestrial ecosystem plays a crucial role to sink the atmospheric CO_2 . Net Primary Productivity (NPP) or vegetation carbon storage is the process to generate chemical energy in presence of solar energy received at canopy level which converted through the process of photosynthesis. This process is the main source of food for the earth's

heterotrophic organism and human being (Imhoff et al., 2004). Climate change and climate related extreme events such as drought have significant impact on global carbon balance (Ji and Peters, 2003; Ciais et al., 2005).

In arid and semi-arid regions, drought is a common limiting factor on NPP. Drought was described as a complex natural disaster and not been identified yet precisely and universally (Wilhite and Donald, 2000). Drought events influence the plant development and leading to substantial reduction in plant growth rate and biomass accumulation. Drought can be described based on duration, intensity and spatial extent. Precipitation can be a proxy to describe the drought as it is the main source of water in the soil. Drought significantly reduces the terrestrial productivity and sink capacity at ecosystem level. Many studies have revealed that global drought events and NPP has a strong correlation using MODerate resolution Imaging spectrometer (MODIS) and Palmer Drought Severity Index (PDSI) (Zhao and Running, 2010). In recent past, droughts in Europe (2003), Australia (2002–2009),

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Amazonia (2005, 2010) had impacted the plant productivity (Zhao and Running, 2010). Drought affects the plant photosynthesis in significant way.

In the recent decade, the frequency, duration and severity of drought have increased substantially on global scale (Dai, 2011), especially in arid and semi-arid regions (Solomon, 2007). It is projected by climate models that future droughts can be stronger in magnitudes, long in durations, and higher in frequencies (Sheffield and Wood, 2006). Future droughts probably have strong impact on the biogeochemical cycle (Parmesan, 2006; Sheffield and Wood, 2012). The major effect of drought is reduction in photosynthesis which lead to decrease in leaf expansion, premature leaf senescence, impaired photosynthetic machinery and food production (Wahid et al., 2005). Under limited availability of soil water, the first option for plant is to close stomata (Cornic and Massacci, 1996) which decreases the inflow rate of CO_2 into the leaves (Farooq et al., 2009).

In order to assess the drought at global or regional level, several drought indices have been developed such as Palmer Drought Severity Index (PDSI) (Ji and Peters, 2003; Rhee et al., 2010), Standard Precipitation Index (SPI) (McKee et al., 1993). PSDI was widely used because of more physical significance (Ji and Peters, 2003; Rhee et al., 2010). However, SPI is easy to calculate in different timescales. The different timescales are very important with SPEI to represent the different types of drought (McKee et al., 1993). As per World Meteorological Organization (WMO), SPI is the standard drought index. SPEI is similar algorithm as SPI but it includes temperature to calculate potential evapotranspiration. Therefore, present study has utilized 1, 3, 6, 12- months SPEI to evaluate the impacts of drought on vegetation productivity at the regional scale.

Several studies were done over the country level NPP (Nayak et al., 2010; Bala et al., 2010). However, the study with the focus on arid and semi-arid regions are not available. The variability of terrestrial vegetation productivity over arid and semi-arid regions due to single factor of drought is not well understood. Therefore, present study focuses over the arid and semi-arid regions of Gujarat, India. The objectives of the study are (i) To find the appropriate SPEI time scale which can represent the impact of drought on vegetation productivity (ii) To investigate, the relation between temporal changes in NPP associated with moisture variability and (iii) To validate the vegetation carbon storage estimated from CASA model with ground based biomass data.

2. Study area

In India, drought prone areas are spread about one third of country, affecting 50 million peoples annually (NCMD, 2010). In north-west India, large area falls under arid and semi arid regions, including Gujarat.

The present study is carried out over the state of Gujarat which is situated in western part of India. The region has the largest coastline of 1600 km. More than 75% of area is considered as an arid and semi-arid (ICAR, 2005). The region is geographically situated between latitude 20.07° N - 24.43° N and longitude 68.10° E - 74.29° E (Fig. 1). The region has total geographical area 0.196 million square km which is about 5.96% of the country's geographical area. The region of Gujarat has wide variability in climate such as arid, semi-arid and sub-humid tropical monsoon types. About 60% area and 99 blocks are subjected to frequent droughts (Bandyopadhyay et al., 2016). The region is characterized by seven agro-climatic zones (ACZ) (Basu and Guha, 1996). Each zone shows the large variability in seasonal rainfall, climate and soil types. The drought prone areas are spread over all the agro-climatic zones. The details of the different Agro Climatic Zones (ACZ) are provided in Table 1.

3. Data sources and method

3.1. Remote sensing data

The MODIS (MOD13Q1) 250 m Normalized Difference Vegetation Index (NDVI) data from 2001 to 2013 are obtained from university of Natural Resources and Life Sciences, Vienna (<http://ivfl-info.boku.ac.at/index.php/eo-data-processing/dataprocess-global>) for the analysis. The MOD13Q1 datasets are atmospherically corrected (Vermote et al., 2002). The datasets are composed of the best observations during 16 days period which are associated with overall pixel quality (low view angle, aerosol content, absence of cloud shadows/clouds) (Justice et al., 2002). The MODIS datasets were further smooth with Whittaker smoother algorithm to reduce the noise level, clouds and cloud shadow contamination, (Atzberger and Eilers, 2011; Vuolo et al., 2012).

3.2. Meteorological data and land use data

National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) meteorological data sets from 2001 to 2013 for the minimum temperature, maximum temperature, and solar radiation are obtained from the Texas A&M University (<http://globalweather.tamu.edu>). The monthly time series of rainfall data for the same period are obtained from Tropical Rainfall Measuring Mission (TRMM - 3B43 Version 7). The biome wise maximum light use efficiency is an important parameter in CASA model. The spatial characterization of land is required in CASA model to set the biome specific maximum light use efficiency value. Therefore, the required land use land cover dataset are obtained from Oak Ridge National Laboratories (ORNL) Distributed Active Archive Center (DAAC) (Roy et al., 2016). The dataset are classified according to the International Geosphere-Biosphere Programme (IGBP) classification scheme.

3.3. SPEI index

The latest Standard Precipitation Evapotranspiration Index (SPEI) version 2.4 dataset <http://digital.csic.es/handle/10261/128892> are utilized for identifying the droughts. SPEI is calculated from the temperature and precipitation datasets which uses simple water balance model developed by Thornthwaite (1948). SPEI v2.4 is based on CRU TS 3.23 monthly gridded Potential Evapotranspiration (PET) and temperature datasets. SPEI is more capable in capturing the effects of extreme temperature and temperature variability than Standard Precipitation Index (SPI) on assessment of drought under global warming scenario (Bortscheller, 2010; Beguería et al., 2010).

SPEI has more advantage to capture droughts at various time scales than Palmer Drought Severity Index (PDSI) which is more crucial part for drought monitoring (Vicente-Serrano et al., 2010). The Penman – Monteith method is used for PET calculation. SPEI can be calculated at different time scales and the scales typically used are 1-, 3-, 6, 12 and 24 months. The 3-, 5- and 6- months SPEI indicate the soil moisture (Ji and Peters, 2003; Hirschi et al., 2011) while 2–3 months SPEI represents the agriculture drought (Mishra and Desai, 2005). Different time scales SPEI 1, 3, 6 and 12 are utilized to capture the moisture variability in the soil from the surface to deep root depth. The monthly anomalies of NPP and SPEI value are generated for all months in 2001–2013. The Pearson correlation coefficients are calculated between anomalies of NPP and 1,3,6 and 12 months SPEI.

3.4. Model datasets

NDVI, meteorology (temperature, precipitation and solar radiation), and land use data sets are required to simulate the NPP in CASA model. The data sets are obtained from different sources and at different spatial resolutions. However, all data sets are required at the same spatial resolution as MODIS NDVI 250 m. Therefore, inverse distance weighted

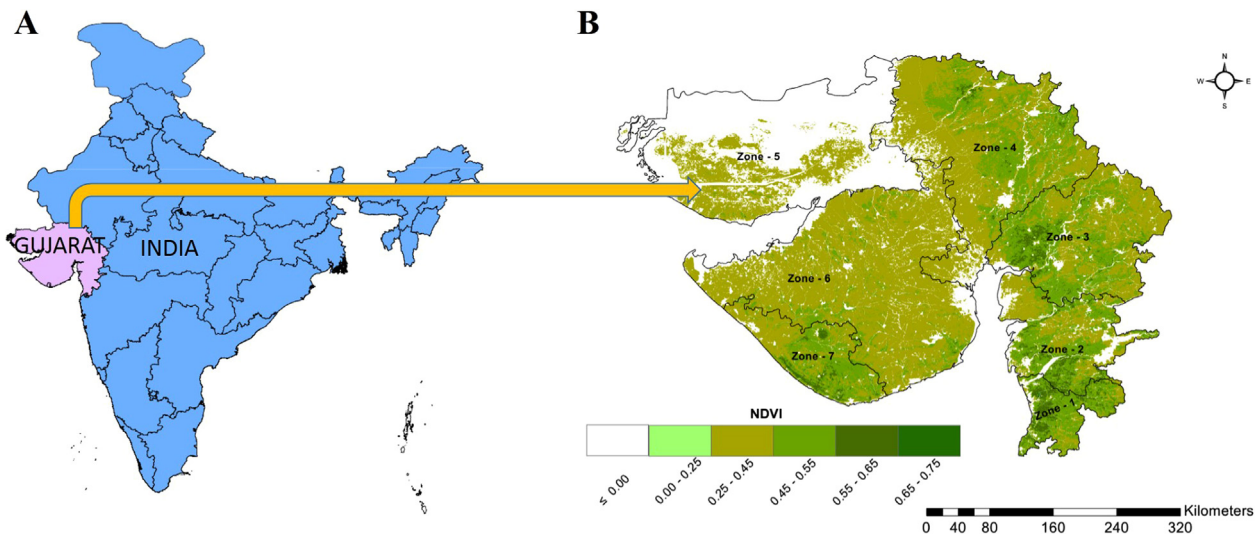


Fig. 1. (A) Map of India showing Gujarat. (B) Spatial variation of annual mean NDVI for 2001–2013 over Gujarat. The inside boundary shows agroclimatic zones of Gujarat.

(IDW) interpolation method is used (Yang et al., 2015) to interpolate all the datasets at MODIS NDVI 250 m resolution for generating the model inputs.

3.5. CASA for calculation NPP

In past decade, several ecosystem models have been developed to calculate NPP at the global and regional scales. Among all models, Carnegie Ames Stanford Approach (CASA) model is one of the satellite based model which has been widely used to evaluate the global and regional NPP. The model was utilized over India (Nayak et al., 2010), United States (Lobell et al., 2002) and on global scale by Potter et al. (1993). CASA is the only ecosystem model that calculates directly NPP. It does not separately calculate GPP and avoids the calculation of respiration (McCallum et al., 2009). In present study, CASA model derived NPP is utilized to understand the impact of drought on terrestrial vegetation productivity.

The CASA model requires several parameters to derive the NPP. It can be classified into two categories (i) Absorbed Photosynthetically Active Radiation (APAR) and (ii) light use efficiency (LUE). CASA model requires meteorological parameters e.g., temperature, precipitation, solar radiation and NDVI data sets as an input to derive NPP. In CASA model, NPP is a product of an amount of Absorbed Photosynthetically Active Radiation (APAR) which is received at canopy level and light use efficiency that is converted to plant biomass. NPP is estimated in CASA model as:

$$NPP(x, t) = APAR \times \epsilon \quad (1)$$

NPP(x, t) is the net primary production by vegetation at location (x)

in the month (t). APAR is absorbed photosynthetically active radiation. APAR is fraction of photosynthetically active radiation (FPAR) and solar irradiance. ϵ is the light use efficiency (LUE) which is governed by temperature and water scalars.

APAR is the product of total solar irradiance and fraction of incoming PAR intercepted by green vegetation (FPAR)

$$APAR(x, t) = FPAR(x, t) \times S(x, t) \times 0.5 \quad (2)$$

Where FPAR is the fraction of photosynthetically active radiation. $S(x, t)$ is the total solar irradiance at given location (x) and time (t) (MJm^{-2}). 0.5 is the ratio of the total solar radiation. FPAR is calculated as a linear function between NDVI and FPAR (Ruimy et al., 1994):

$$FPAR = \frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min}) \times (FPAR_{max} - FPAR_{min}) + FPAR_{min}} \quad (3)$$

Where $NDVI_{max}$ and $NDVI_{min}$ are considered fully vegetation covered pixel and almost no vegetation covered pixel respectively. $FPAR_{max}$ and $FPAR_{min}$ are the maximum and minimum FPAR which are set as 0.95 and 0.001 respectively.

Light use efficiency (ϵ) is effected by temperature and available soil moisture and can be expressed by following Eq. (4)

$$\epsilon = \epsilon^* \times T_1(x, t) \times T_2(x, t) \times W(x, t) \quad (4)$$

Where ϵ^* is the maximum light use efficiency of the plants. On global scale, ϵ^* was used $0.389 gC MJ^{-1}$ for all vegetation types (Potter et al., 1993). ϵ^* value is influenced by number of environmental factors. However, several studies suggested that constant ϵ^* value for all vegetation types can underestimate the NPP (Running et al., 2000; Peng,

Table 1
Agro-climatic zones of Gujarat.

Zones	Zones name	Districts covered by zones	Rainfall (mm)	Climate	Soil
Zone - 1	Southern Hills	Dangs, Bulsar	1793	Semi-arid to Dry Sub humid	Deep black, coastal sub humid alluvial
Zone - 2	Southern Gujarat	Surat, Bharuch	974	Semi-arid to Dry Sub humid	Deep black, coastal sub humid alluvial
Zone - 3	Middle Gujarat	Baroda, Kheda, Panchmahals	904	Semi-arid	Medium black
Zone - 4	North Gujarat	Ahmedabad, Mehsana, Gandhinagar, Sabarkantha, Banaskantha	735	Arid to semi-arid	Grey brown, Coastal alluvium
Zone - 5	North West Arid	Kutch	340	Arid to semi-arid	Grey Brown Deltaic alluvium
Zone - 6	North Saurashtra	Amreli, Bhavnagar, Jamnagar, Rajkot, Surendranagar	537	Dry sub-humid	Medium black Calcareous
Zone - 7	South Saurashtra	Junagarh, Porbandar	844	Dry sub-humid	Coastal alluvium

2000). Therefore, we have used biome wise ϵ^* values for different vegetations. Biome wise ϵ^* values for different vegetation types are obtain from Zhang et al. (2014) in which ϵ^* were calibrated using flux tower data. T_1 and T_2 temperature stress scalars are calculated as per (Potter et al., 1993).

$$W(x, t) = 0.5 + 0.5 \times \frac{ET_a}{ET_p} \quad (5)$$

$W(x, t)$ is water stress factor which is proxy for soil moisture at given location (x) and time (t). $W(x, t)$ scalar is the ratio of actual (ET_a) and potential (ET_p) evapotranspiration. $W(x, t)$ scalar is in range from 0.5 (extreme dry) to 1 (extreme moist). ET_a and ET_p are calculated by regional evapotranspiration model (Zhou, 1995, 1996). ET_a can be expressed by Eq. (6).

$$ET_a = \frac{P(x, t) \times R(x, t) \times [P(x, t)^2 + R(x, t)^2 + P(x, t) \times R(x, t)]}{[P(x, t) + R(x, t)] \times [P(x, t)^2 + R(x, t)^2]} \quad (6)$$

Where $R(x, t)$ is the net solar radiation ($MJm^2/month$). $P(x, t)$ is the monthly precipitation (mm/month). The potential evapotranspiration is given by equation no (7),

$$ET_p(x, t) = \frac{ET_a(x, t) + E_o(x, t)}{2} \quad (7)$$

Where $E_o(x, t) = 16 \times [10 \times T(x, t)/I(x)]^{\alpha(x)}$ and $\alpha(x)$ and $I(x)$ can be calculated by Eq. (9),

$$\alpha(x) = (0.6751(x)^3 - 77.11(x)^2 + 179201(x) + 492390) \times 10^{-6} \quad (8)$$

Where

$$I(x) = \sum_{i=1}^{12} (T(x, t)/5)^{1.514} \quad (9)$$

$I(x)$ is the total heat index in a given year and $T(x, t)$ is the monthly average temperature at given area.

4. Results and discussions

4.1. Temporal variation in SPEI and NPP

NPP is one of the key indicator which reflects the change in vegetation at global and regional levels. CASA derived NPP over arid and semi-arid regions of Gujarat, India shows an increasing trend of $0.2TgC/Yr^{-1}$ which is about 2 % per year during the period of 2001–2013. Despite the many deficiency rainfall year during the period of 2001–2013, vegetation productivity shows an increasing trend. An increasing trend of 3.9% in NPP was also found by Bala et al. (2010) during 1982–2006. The temporal pattern of NPP and different time scales 1, 3, 6, 12 months SPEI are shown in Fig. 3. Poor performance of monsoon results the drought in the region. The region has faced many deficiency in rainfall which occurred in every 1–2 years interval (Fig. 2). However, the largest deficiency in rainfall (45%) was occurred during 2002. The other rainfall deficient years were 2001 (21%), 2004 (17%), 2008 (17%), 2009 (15%), and 2012 (34%). All the rainfall deficit years were El-Niño years expect 2001. Due to consecutive

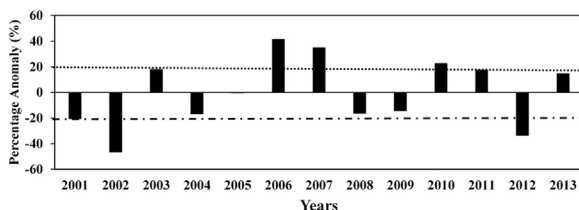


Fig. 2. Percentage departure of seasonal rainfall of Gujarat region during 2001–2013.

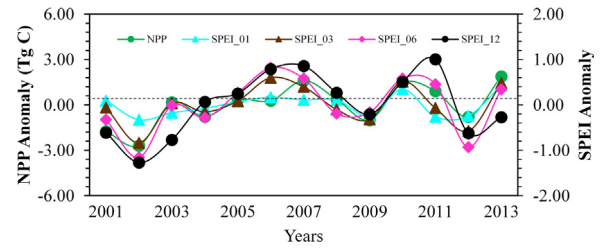


Fig. 3. Annual variation of NPP and different time scales SPEI over Gujarat, India.

droughts during 2001 and 2002, the NPP is significantly reduced by 16% (1.8 TgC) and 24% (2.7 TgC) in 2001 and 2002 respectively.

Due to drought, the temperature extreme and heat waves were observed in the region (Bandyopadhyay et al., 2016). Heat waves and temperature extreme subsequently have impacted the vegetation productivity. This gives rise to inphase relation between NPP and SPEI. The climatic factors such as local wind, rainfall pattern are strongly influenced over the region of Gujarat in drought years (Bandyopadhyay et al., 2016). The deficiency in rainfall is well reconstructed by the different time scale SPEI. However, the capability of different time scale SPEI for capturing the drought over arid and semi-arid regions is different from each other. The temporal variation of SPEI also shows an increasing trend similar to NPP. Due to deficiency in rainfall, it is observed that NPP is reduced significantly over the region by 1.8, 2.7, 0.8, 1.00, 0.8 TgC during 2001, 2002, 2004, 2009 and 2012 respectively. Despite being deficit rainfall during 2008, vegetation productivity showed positive trend. As during the 2008, the heat waves were remarkably lower (the region had experienced heat wave only for 4 days) compare to other drought years (where >25 heat waves events were reported) (Bandyopadhyay et al., 2016). It indicates that heat wave also plays a major limiting factors in vegetation productivity in arid and semi-arid regions. During drought years, inadequate rainfall and acute shortage of soil moisture cause extreme crop stress, which lead to decrease in the rate of productivity. It was reported that most part of the north Gujarat faced rise in temperature coupled with rainfall deficiency in last decade 2001–2010 (Bandyopadhyay et al., 2016).

The frequency of heat wave was remarkably higher in the drought years. Consequently, it severely damaged the crop health and resulted significant reduction in crop yield (Bandyopadhyay et al., 2015). Heat wave affect the crop production by raising of air and land temperatures. The crop exposed to extreme heat may die quickly due to excessive evapotranspiration and less moisture supply. Reduction in the NPP in Europe was also caused by heat and drought during 2003 (Ciais et al., 2005). During the drought years, extreme temperature has major limitation on plants which substantially reduce the plant productivity. Positive trends of 3%, 2% and 15% in NPP are also observed during 2005, 2006 and 2007 respectively, due to three successive normal monsoon (Fig. 2).

4.2. Impact of drought on net primary production

4.2.1. Impact over arid and semi-arid region

The correlation coefficients between NPP and different time scale SPEI are shown in Table 2. The correlation coefficients for different time scales of SPEI and NPP shows a good agreement (>0.70) except 1 month SPEI (<0.70). The correlation coefficients are found 0.65, 0.81, 0.82, and 0.70 for SPEI 1, 3, 6, 12 months respectively. The 3 and 6 months SPEI show the higher correlation coefficients with NPP with significance >90%. Correlation coefficient values are increasing along with the time lag increased and the value is decreased for 12 months SPEI time scale. On a global scale, NPP is found to have high correlation with lower time scale SPEI (1–3 months) (Chen et al., 2013). In the present study, the NPP is found to have higher correlation ($r = 0.82$,

Table 2

Correlation coefficient between annual anomalies of NPP and SPEI for the entire region and different agro climatic zones. For entire region, correlation coefficient of 0.65, 0.81, 0.82, 0.70 indicate significance >99%.

SPEI	Gujarat region	Zone-1	Zone-2	Zone-3	Zone-4	Zone-5	Zone-6	Zone-7
1	0.65	0.29	0.50	0.45	0.49	0.54	0.63	0.71
3	0.81	0.59	0.72	0.66	0.64	0.72	0.80	0.76
6	0.82	0.77	0.80	0.73	0.70	0.71	0.76	0.76
12	0.70	0.49	0.60	0.64	0.62	0.73	0.60	0.61

$p > 90\%$) with medium time scale (6 months) SPEI over the region. The higher correlations are found with medium time scale of SPEI which can be due to medium range (3–5 months) crop growing period over the region.

4.2.2. Spatial pattern of drought impact analysis

The high correlation ($r = 0.82$) with high significance $\geq 99\%$ are found between the 6 months timescale SPEI and NPP anomalies. Therefore, it is observed that 6 -month SPEI will be suitable for the impact analysis in the arid and semi-arid regions. In the present analysis, 6 -months SPEI is spatially correlated with NPP. Fig. 4 shows the 250 m gridded correlation between 6-months SPEI and NPP for the period 2001–2013. The regions shown in white on the map are the desert or land having no vegetations as correlations are not estimated over the no vegetation regions. The maximum area shows a significant positive correlation ($r \geq 0.8$, significance >95%) between NPP and SPEI. As these parts of the region are under arid climate and near tropic of cancer which result the hottest part of the region. Therefore, slight variation of rainfall can have the significant impact on vegetation productivity in these parts. These parts mainly depend on monsoon rain

when compare to the other parts of the region. The southern and southwest regions show the lower correlation (<0.6), as the regions have sub-humid climate. It is observed that the north and northwestern regions are more sensitive to the drought, while southern part of the region is less sensitive. The northern part of the region faces rising in temperature (Bandyopadhyay et al., 2016) and it is near to the Thar desert. Therefore, the geographical condition made the region too hot which turned to higher evapotranspiration losses and resulted to the dry region. Some part of southwest and northwest regions show the negative correlation between NPP and SPEI (-0.3 to 0).

The negatively correlated regions indicate that NPP is less affected by rainfall deficiency. This is attributed to the presence of some planted mangroves and drought tolerance grasses, which are not affected by the drought. The northern and western parts of regions are dominated by agriculture land. In southern and some part of southwestern region had less impacted by the drought. As the annual rainfall in the southern region is high (1.8 times) when compared to other regions and the region dominated by forest cover. In arid and semi-arid regions, agriculture land is more sensitive to drought than other land use classes. In order to sustain the vegetation carbon storage and productivity under frequent droughts in the region, the good management practices are needed. The increase in the water storage capacity and judicious use of water can provide good management practices for sustainable production.

4.3. NPP and SPEI in agro-climatic zones

Understand the region more explicitly, The relationship between NPP and SPEI in different Agro-Climatic Zones (ACZ) are utilized. Table 1 shows zone wise physical and climatic variability. The region is divided into seven ACZs (Basu and Guha, 1996). The soil types vary from deep black to grey brown. Zone-1 is the wettest zone receives maximum annual rainfall (1793 mm) during the southwest monsoon

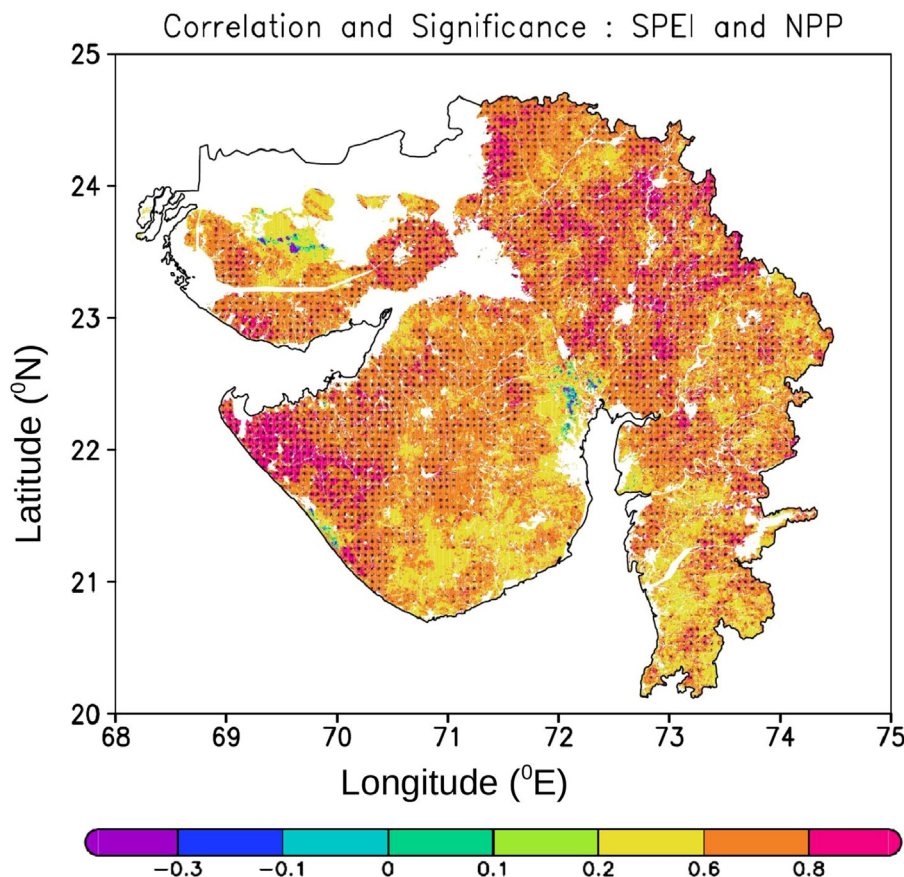


Fig. 4. Spatial variation in correlation coefficient between annual anomalies of Net Primary Production (NPP) and 6 months Standardized Precipitation Evapotranspiration Index (SPEI) over Gujarat. Dots indicate correlations at 95% significance level. The regions shown in white on the map are the desert or land having no vegetations.

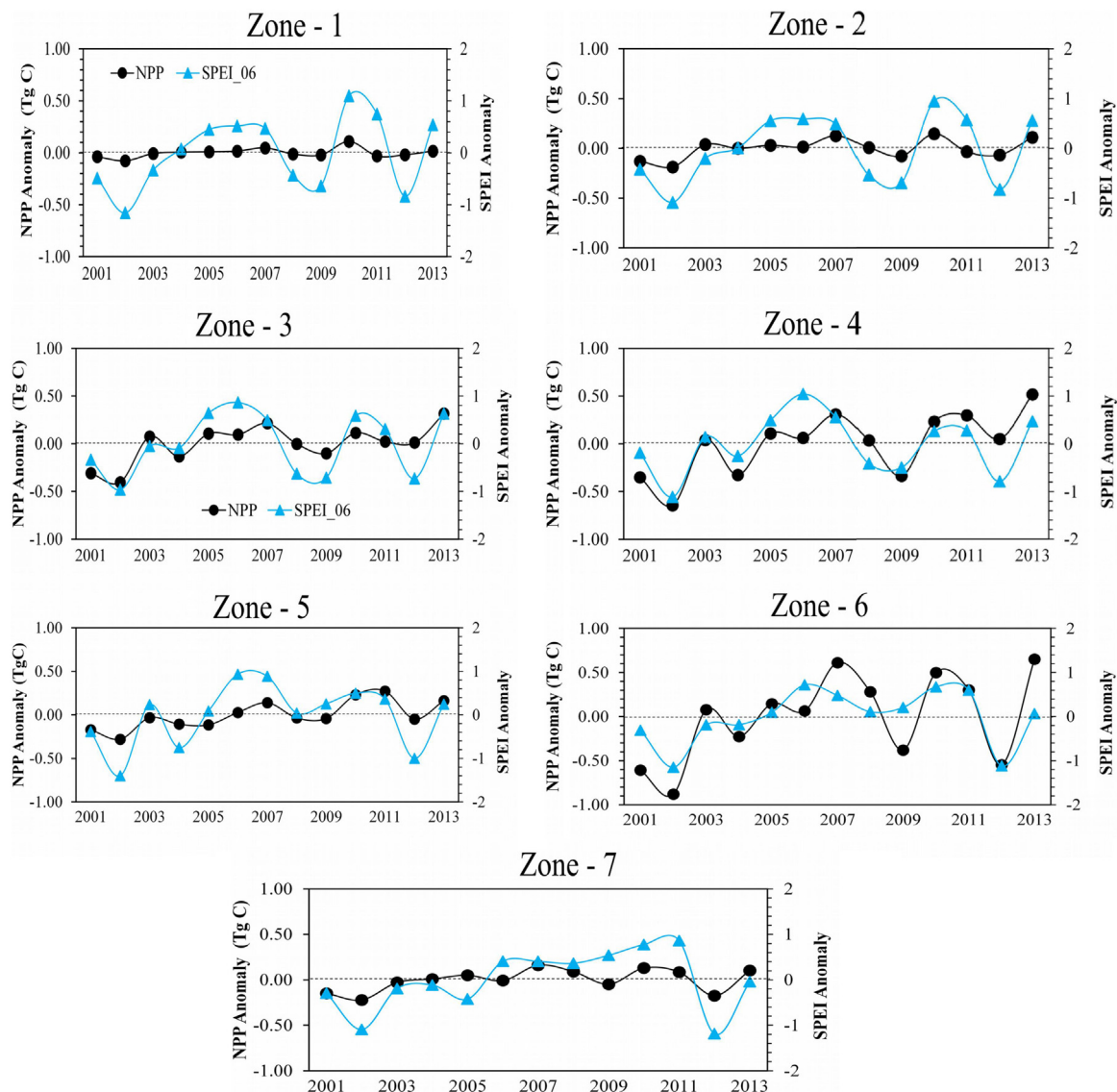


Fig. 5. Annual variation of NPP and SPEI anomalies over different agroclimatic zones of Gujarat.

season, while zone-5 is the arid zone and receives very less annual rainfall (340 mm). The zone wise NPP and 6-month SPEI anomaly is analyzed for further understanding the impact of drought on vegetation carbon storage. The annual anomalies of NPP and 6-months SPEI for different zones are shown in Fig. 5. The similar behavior of NPP and SPEI are found over different zones.

It is observed that the dry sub-humid region (Zone-6) is more sensitive to drought. In this zone, reduction in NPP is very high compared to other zones, while semi-arid to dry sub-humid zone (Zone 1) is less sensitive to drought. The Zone-1 is dominated by forest area in which about 43% of the area are under forest and about 63% of area of Zone-6 are under cultivated and agriculture productivity is also high (Pathak, 2006). The land use classes make the zones more or less vulnerable to drought. In zone-6, NPP was declined by 0.61, 0.88, 0.23, 0.38 and 0.55 TgC and in zone-1 by 0.04, 0.08, 0.01, 0.02 and 0.02 TgC during drought years 2001, 2002, 2004, 2009, 2012 respectively. This suggests that impact of drought over cultivated area is relatively higher than other land use classes. ACZ wise analysis can help in identifying the drought affected zones. This result may help to make the zone wise water management policy so that reduction in vegetation productivity can be managed during the drought years.

4.4. Validation of CASA simulated NPP with ground based observations

CASA derived NPP is validated using ground based data. On global scale, most of the study used tower flux data to validate CASA model (Potter et al., 1993). Flux tower data is still not available over the study region. However, flux tower is not directly measuring the NPP, it is measuring the Net Ecosystem Exchange (NEE). Therefore, district wise crop yield data are obtained from state agriculture department and converted the crop yield data to NPP. The details of converting the crop yield to NPP can be found in Nayak et al. (2010). The correlation between simulated NPP with observed data is shown in Fig. 6. The result shows a good agreement ($R^2 = 0.57$) between observed and simulated NPP with significance >99%. Nayak et al. (2010) also found that CASA model and ground based observation showed a good agreement ($R^2 = 0.54$) over western India. This study suggests that CASA model derived NPP is well representing the biomass over the arid and semi-arid regions of India.

5. Conclusion

The impact of drought on NPP is one of the key dynamical process in the global carbon cycle. Drought influences the plant growth rate by

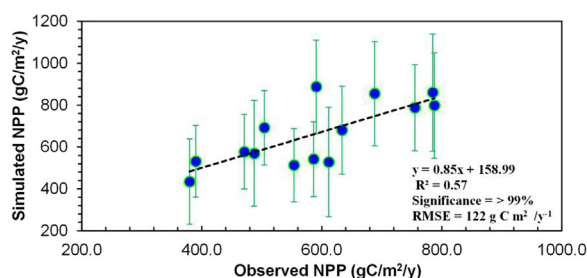


Fig. 6. Validation of CASA simulated NPP with observed NPP.

limiting supply of water. Impact of drought on vegetation productivity is analyzed in arid and semi-arid regions of Gujarat, India using CASA derived NPP and SPEI from 2001 to 2013. The study reveals that

- A statistically significant correlation (>0.8) is found between NPP and different time scale SPEI. Despite the many deficiency in rainfall during the period of 2001–2013, vegetation productivity shows an increasing trend. A significant (significance $>98\%$) increasing trend of 0.2TgC/Yr^{-1} (about 2 % per year) is observed during the period of 2001 – 2013.
- The large deficiency with 45% reduction in rainfall occurred during 2002 followed by others years. All the rainfall deficient years were El-Niño years except 2001. NPP was significantly reduced by 16% (2.7 TgC) and 24% (1.8 TgC) which were attributed to consecutive drought during 2001 and 2002 respectively. Despite the drought during 2008, there was no decrease in vegetation productivity. It suggests that in addition to rainfall, heat waves may also be a major limiting factor in vegetation productivity in arid and semi-arid regions.
- Among different time scales SPEI with NPP anomalies shows higher correlation ($r = 0.82$) at high significant level (significance $\geq 99\%$). The most part of the region shows a significant positive correlation between NPP and 6 months SPEI. The part of northern and south-western regions show higher positive correlation ($r \geq 0.8$, $p > 95\%$) between NPP and SPEI. The southern and other southwest regions show the moderate correlation (<0.6), as the regions have sub-humid climate type.
- ACZs wise analysis suggests that the dry sub-humid region (Zone-6) is more sensitive to drought as reduction in NPP is very high compare to other regions, while semi-arid to dry sub-humid (Zone 1) is less sensitive. The Zone-1 is dominated by forest area, and Zone-6 is rainfed agriculture land with high productivity. Zone wise analysis indicates that the agriculture land is more vulnerable to drought than other land use classes in arid and semi-arid regions.

Such spatial and temporal variability of NPP due to single factor of drought can have important impact on the global carbon balance. This study will be useful in improving the water management policy in drought prone area.

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